Social Delay-Tolerant Network Routing

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Abstract

Routing in mobile delay-tolerant networks faces new challenges such as mobility and the dynamic nature of the network. Social network information may be useful for routing since mobile nodes in the same social network may be encountered more often and thus be more successful at message-passing. Collecting this social network information, however, can be challenging. We compare a social network traced from user encounters with a user-declared social network, and show some of the differences between these two networks.

1 Introduction

As mobile devices, carried by individuals in their everyday lives, become more prevalent, it may be useful to investigate how we can exploit human mobility and proximity in the context of mobile device routing.

One architecture for building applications that make use of this human interaction and proximity is the concept of a Delay-Tolerant Network (DTN) [8]. These are networks where some of the traditional assumptions regarding network links may not hold: they may lack end-to-end connectivity and feature high delays, and typically employ a store-and-forward architecture in order to relay messages. DTNs can provide services and applications in areas where the TCP/IP architecture cannot cope; for instance disaster recovery scenarios or internet kiosks in rural areas.

One important issue in mobile DTNs is how to effectively and efficiently route information. Since nodes may be mobile, static routing tables are inappropriate. Since many applications involve sending to a known destination node, researchers have explored the use of this social network information to build DTN routing tables, recording encounters in order to construct the social network. But recording encounters can be time-consuming and error-prone. Generating the DTN routing table from a user's declared social network, rather than one detected through encounters, may be a simpler approach.

A recent study [14] of these *self-reported social networks* (SRSNs) and *detected social networks* (DSNs) found the two social networks to be similar for conference attendees. Social scientists, however, have found that self-reported and detected social networks may differ [1]. In this paper we compare and observe the differences between these two social networks, in order to gain insight into how a DTN using these networks may perform.

2 Related Work

Many researchers have looked at understanding human mobility and exploiting this for DTN routing. Hui et al. [10] introduce the "Pocket Switched Network"(PSN) in a study of human mobility in conference environments. The rationale for the PSN is that in the absence of any connection to existing infrastructure, passing messages between devices carried by humans could eventually route a message to the intended destination. Subsequent work looks at identifying the correct groups of people to which to forward information so as to improve routing and node efficiency[11, 12].

The Reality Mining project collected location, communication and device-usage behaviour data from 100 human subjects who carried Bluetooth-equipped mobile phones over the course of nine months [6]. This led to an extremely rich dataset, containing over $500{,}000$ hours of data, which, amongst other uses, has been used for understanding forwarding in DTNs [4, 5]

Another significant experimental system is MetroSense, a "people-centric paradigm for urban sensing at the edge of the Internet" [3]. MetroSense leverages existing infrastructure and mobility to opportunistically sense and collect data. They use mobile phones and motes (small wireless sensor nodes) in order to collect sensed data, which are then routed through a sensor-mote-based DTN.

Musolesi et al. use social network theory to create a movement model [15]. Nodes move towards *goals*; points in the simulation space that result from applying an equation to work out the attractiveness of a particular goal. Attractiveness is a function of the social network tie strength and the number of members of the social network that are near that goal. They make the explicit assumption that social network tie strength is a reliable indicator of co-location.

3 Experimental setup

As part of a research project we set up a mobile sensor network comprising mobile IEEE 802.15.4 sensors (T-mote invent devices) carried by 25 human users (22 undergraduates, 5 staff and postgraduates) for a total of 79 days. T-mote invent devices can detect each other within a radius of $\sim$12m. These encounters are stored in the invent devices and are uploaded through basestations to a central database.

We used the participants' *Facebook*[1] social network information to generate a topology . We refer to this as the ***self-reported social network (SRSN)*** following the terminology of [7]. We also generate a topology using the traced encounters to create a social network, similar to [5]. We refer to this as the ***detected social network (DSN)*** following the terminology of [13, 16].

4 Comparing the Social Networks

Before examining the impact of SRSNs versus DSNs on DTN performance, we must answer the question: *Are detected social networks and self-reported social networks similar?* Figure 1(a) and Figure 1(b) show the topologies for the SRSN and DSN. These show some differences between the two networks, but to better understand these differences, we employ methods from social network analysis.

4.1 Structural equivalence

Structural equivalence allows the comparison of ties between nodes (or *actors* in social network analysis terminology) in social networks. Actors who have identical relationship ties to the same group of actors are *structurally equivalent* and are in the same *equivalence class*.

To calculate structural equivalence, we create a *sociomatrix* of the ties between actors; if actor i has a tie to actor j, then the element (i, j) has a value of 1; otherwise the value is 0. If actors i and j are structurally equivalent, the entries in their respective rows and columns of the sociomatrix will be identical (i.e., the Euclidean distance between them is 0). By computing distances between all n actors in the network, we create an $n \times n$ matrix that shows the structural equivalence of each actor.

Using these Euclidean distances as a metric, we can plot *dendrograms* for the social networks. These can be used to understand clustering; each cluster is a set of nodes whose largest intra-group distance is smaller than the distance to the nearest point outside the set. Nodes on the same 'branch' of the dendrogram are considered to have shorter distances between them, and are said to be clustered.

This technique allows us to find nodes that can pass messages to the same group of nodes in the same way. We can consider nodes in the same equivalence cluster to be interchangeable for passing messages to the same group of nodes. We could use this to work out which alternative nodes could be used for message passing, allowing us to fairly distribute message forwarding responsibilities amongst a set of structurally equivalent nodes. This would allow us to maximise battery life of nodes.

4.2 Role equivalence

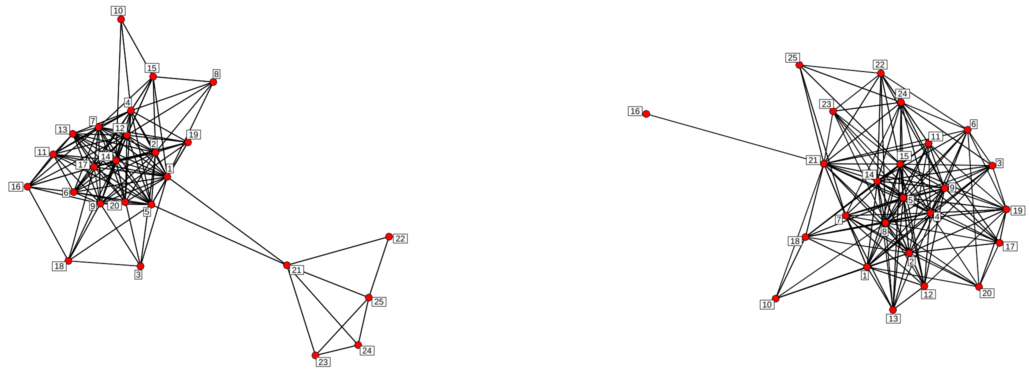
Closely related to the concept of structural equivalence is *role equivalence*. This allows us to further examine clusters in a social network but also compare the clusters between different social networks. Two actors i and j are role equivalent if the collection of ways in which i relates to other actors is the same as the collection of ways in which j relates to other actors [17]. To examine role equivalence graphically, we use *blockmodels* following [18]. Each block in the blockmodel indicates whether the column's actor has equivalent ties to other nodes as the row's actor. For each pair of structural equivalence relationships (node ties), we determine whether a tie exists between the positions of the relationships, i.e., do the ties from actor j match actor i? If there is sufficient overlap to satisfy the equivalence criteria (in our case: is there at least one match in every row and column of i and j's role sets), then a block is added to the blockmodel diagram in the jth column for the ith row.

By analysing role equivalence we hope to classify nodes according to their ability to transfer messages, which will allow selection of nodes for message forwarding according to their suitability of passing a message to the destination.

4.3 Betweenness

The third social network analysis tool that we employ is the notion of betweenness centrality. Betweenness centrality represents the control of information flow through a network. For all unordered pairs of nodes i, j, k where $i \neq j \neq k$, B is the probability that k falls on a randomly-selected path linking i and j. The sum of B is the betweenness of k within the network [9]. In other words, betweenness allows us to calculate how many nodes are reachable indirectly through a given node's network. We are most concerned with *ego-centric* betweenness; the betweenness of a node from its view of the social network with it at the centre. This is useful since we can see how much information a node has control over in the network, and ego-centric betweenness can be calculated by the node itself, since global knowledge of the network is not required.

[1] http://www.facebook.com/



(a) The SRSN graph. There are two groups of nodes, the small group is the staff and postgraduates, and the large group is the undergradaute student group. Ties in this social networks are Facebook “friend” connections.

(b) The DSN graph. At first glance it appears all participants bar one seem to be in the same group. On average nodes in the DSN have more ties. Ties in this social network are real world encounters.

Figure 1. The topologies of the SRSN and DSN. The numbers are consistent across both plots, i.e. node 1 in the SRSN is also node 1 in the DSN.

Betweenness can be used to work out whether a node is likely to be given many message to forward in a DTN. A high betweenness might then lead to a high chance of the node being required to forward messages and consequentially running low on power.

4.4 Social Network Analysis

Figure 1(a) indicates that in the SRSN, there is a large group of nodes and a smaller set of 5 nodes, where one of these (node 21) bridges to the main group via two ties. In the large group of nodes we observe nodes around the edge and several more popular nodes in the centre. By contrast, the DSN shows a much less obvious divide between social groups (Figure 1(b)). There is one node with only one tie to the rest, but there is generally a higher level of connectivity in the DSN. Overall, however, it is difficult to distinguish any important groups using these topology diagrams.

4.4.1 Structural equivalence

To understand the structure of the networks, we examine the dendrograms of the network structure (Figure 2(a) and Figure 2(b)). The height of the dendrogram is given by Euclidean distance. The values are then clustered bottom up, where each mutual cluster is a set of nodes whose largest intra-group distance is smaller than the distance to the nearest point outside the set.

The SRSN dendrogram (Figure 2(a)) shows three clusters of nodes. The smallest group (nodes $22, 23, 24, 21, 25$) matches with the small group on the network diagram. The other two groups are harder to distinguish on the network graph, and so we use blockmodels to examine the breakdown of the social roles.

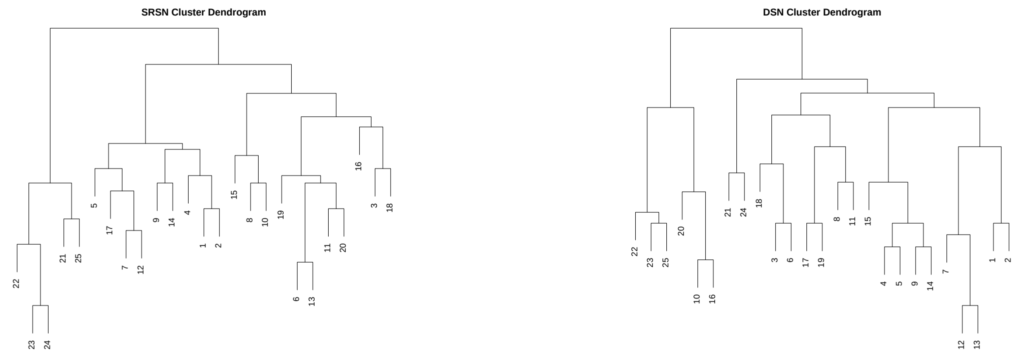
4.4.2 Role Equivalence

The SRSN blockmodel (Figure 3(a)) indicates three roles, each of which can be seen as a cluster in the dendrogram, or as a section of the blockmodel. We found four weakly-defined roles in the DSN blockmodel(Figure 3(b)).

On average, nodes in the DSN have a greater number of ties than in the SRSN. In both cases the roles indicated in the blockmodel confirm the clusters described in the respective dendrograms, and also help distinguish the roles more clearly. The roles are less well defined in the DSN, since the blockmodel does not show as obvious divisions as in the SRSN. The SRSN's roles seem to form more blocky structures with similar relations to each other, and with clear boundaries. In the DSN, however, divisions seem to be distinguished by number of ties to the centre of the network. This is a feature of the blockmodel that would not have been obvious from simply inspecting the topology diagrams.

4.4.3 Betweenness

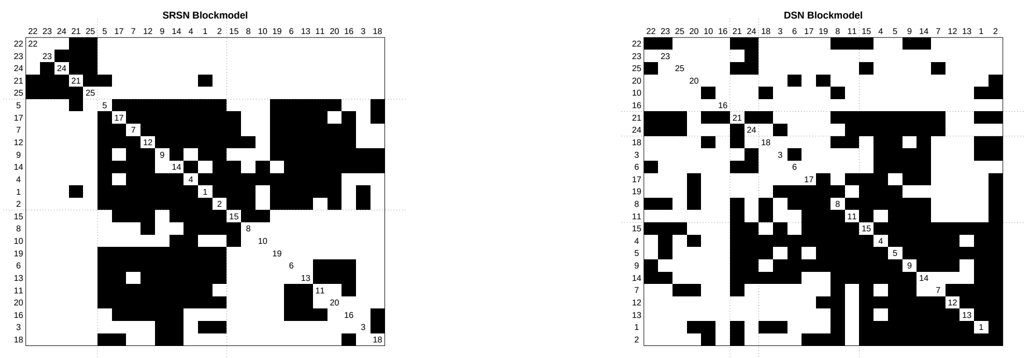
Figure 4(b) and Figure 4(a) show the distributions of egocentric betweenness for the DSN and SRSN respectively. The two distributions differ and the median betweenness is higher for nodes in the DSN (3.30 compared to 1.25 for the SRSN). This indicates that nodes have more control over information in the DSN.



(a) Dendrogram for SRSN, clustered by Euclidean distance. We observe three different clusters of nodes.

(b) Dendrogram for DSN, clustered by Euclidean distance. We observe four different clusters of nodes.

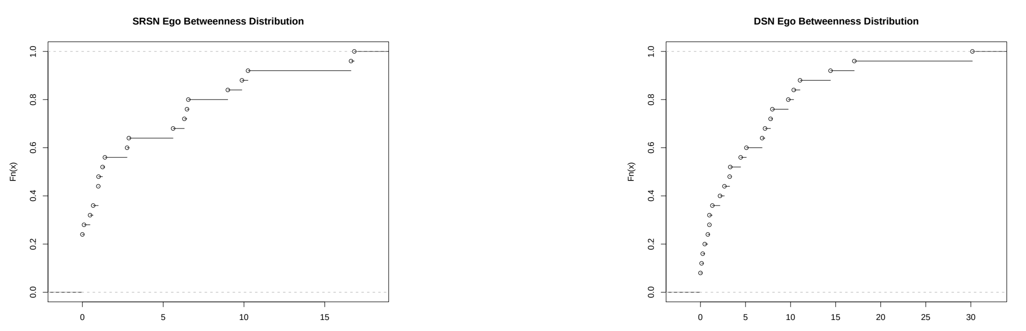
Figure 2. The equivalence clustering Euclidean distance dendrograms.



(a) Blockmodel for the SRSN. There are three clearly-defined roles within the social network.

(b) Blockmodel for the DSN. There are four weakly-defined roles.

Figure 3. Blockmodels of role equivalence for the SRSN and DSN. Dotted lines indicate role divisions.



(a) We see that node in the SRSN on average have a lower betweenness than the DSN. (Median of 1.25).

(b) We see that on average nodes in the DSN have a higher betweenness. (Median of 3.30).

Figure 4. Distribution of ego betweenness for DSN and SRSN.

5 Conclusions and Future work

This paper has explored the differences between two social networks for the same set of users: the detected and self-reported social networks. These networks appear to differ in terms of structure and role equivalence, as well as the distributions of node betweenness. In previous work we have explored the effect of these social networks on DTN routing and have found that the SRSN delivers good performance at low cost [2]. We believe that future mobile communications networks have much to learn from social network analysis. There are, however, many questions left to answer.

In future work we would like to explore other techniques for social network analysis, in order to gain further insight into how social networks can affect DTN performance. In particular we need to determine online and efficient analysis techniques that can be performed by nodes in the network, rather than the offline analysis which we have presented here.

We also intend to further study the network structure in order to best exploit the message-passing opportunities along social ties. Which roles and groups should be used for message-passing? Does a users' role change over time? Should we use the SRSN, the DSN, or a combination of the two?

We would also like to investigate how the analysis of social networks can provide applications with the information on the expected properties of the DTN, thus allowing applications to make informed decisions based on the expected performance of message sending. For example, if an application knew the expected delay, or delivery cost or expected chance of delivery, it could adjust the frequency of messages being sent. If an application knew that it was in the centre of a network and likely a bottleneck it could take measures to reduce message throughput or advertise this to nodes so that they would reduce messages being routed through the congested node. At the same time, the collection of this information needs to be weighed against the privacy implications of sharing this social network information, and another area of future work is studying the tradeoff between privacy and network performance.

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